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Office Market Dynamics in Madrid: Modelling with a Single-Equation Error Correction Mechanism

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This paper seeks to explain the office market dynamics in Madrid by using cointegration models. Specifically, we focus on the equilibrium path of stock, vacancy rate and letting rents, and feedback with two exogenous economic determinants, namely, service sector employment and gross domestic product. We apply for the first time a single-equation error correction mechanism (ECM) to a system of equations for the commercial property market of Madrid and examine its accuracy when compared to the more frequently used classical two-step ECM. The main findings to emerge from our empirical analysis are that rents and vacancy rates react rapidly when they do not correspond to their equilibrium level. Stock, as expected, responds more slowly when it does not correspond to its long-term path. We draw on quarterly observations for the Madrid market between 2001:Q1 and 2015:Q2.

Keywords

Error Correction Model, Office Market, Single-Equation Error Correction Mechanism

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1. Introduction

Since the 1980s, the study of commercial property markets (retail shops, warehouses and offices) has gained momentum in the economics literature, leveraging on earlier research that analyse the economics of residential real estate. These studies began in the 1950s and 60s with a price estimation of the US housing market (Blank & Winnick, 1953) and an examination of the effects of economic cycles in the US residential construction sector (Alberts, 1962). More specifically, the seeds of the economic analysis of the non-residential markets were sown in the 1970s by Pritchett (1977) and Ferri (1977). The global economic boom of the late 1980s and early 90s and its impact on the development of offices, high street shops and shopping centres, as well as on industrial warehouses and logistics facilities, have coincided with the development of the necessary conditions for the investigation of non-residential property markets (Ball et al., 1998), namely:

- The growing availability of longer time series of supply, price and demand data for commercial property markets; and,

- The development and diffusion of new statistical analysis tools, including cointegration and error correction models.

It was against this backdrop that the seminal works on cycles in office markets were published in the US and the UK by Rosen (1984) and Wheaton (1987). These studies analyse the mechanisms of adjustment of real estate variables (rent, availability, absorption of space and construction) and their long and short run relationships with macroeconomic variables. In wake of these studies, a substantial body of literature has arisen, and extended the analysis to other European markets (see Hoesli, 2016 for a survey).

The Spanish property market is an interesting case study due to the collapse after the overshooting from a long-term price increase of Spanish real estate prices. Indeed, house prices in Spain showed one of the largest cumulative growth rates among the Organisation for Economic Co-operation and Development (OECD) during the 1990s, which were supported by rapid economic expansion, strong employment growth, an immigration boom, and low real interest rates. With the abrupt drying up of funding since mid-2007, these factors have eroded quickly. Most of the empirical work on the assessment of the "long-run equilibrium" level of housing prices find evidence of a misalignment with respect to the estimated equilibrium (see, for e.g., Ayuso and Restoy, 2003, Martínez-Pagés and Maza, 2003, International Monetary Fund, 2004, The Economist, 2005 and Caruana, 2007).

In the case of the Spanish commercial property market, published research is not abundant. Mention should be made, however, of the studies of Brounen and Jennen (2009b) and Fuerst and McAllister (2010), which seek to explain the rent dynamics across Europe (specifically, in 10 and 19 city markets – including Madrid, respectively). The former authors use an error correction model on maximum rents and the latter use linear regression models to analyse the elasticity of supply.

The objective of this paper is to undertake a time series analysis (by using cointegration and error correction models) to describe the dynamics of vacant office space, delivery of new office stock (office stock variation) and average rents in terms of elasticities as well as responses to deviations in rents and vacancy rates. Our contribution to the empirical literature is twofold. First, we propose models capable of predicting future market developments, identifying phases in which rents have appreciated or depreciated against the long-run equilibrium, and quantifying the possible over- or under-valuation of the cyclic property type. Second, we measure the forecasting performance of the two-stage and the single-equation error correction mechanisms (ECMs) to select the best modelling system to analyze rents, vacancy rates and stock changes.

In our study, we adapt the model developed by Hendershott et al. (2013, hereafter HJM) to the office market in Madrid. Two specific models are estimated and compared: on the one hand, the ECM (Engle and Granger 1987) and, on the other hand, the single-equation ECM (Banerjee et al., 1993). Our study shows that the best model for conducting dynamic forecasting is that of Engle and Granger.

Following on from this introduction, the second section outlines our commercial property market model and the third section details the econometric models employed. The fourth section describes the data used and the fifth and sixth present the econometric approach and the results of the estimated models, respectively. The seventh section compares the results of the two estimation methodologies and, finally, we present our concluding remarks.

2. Conceptual Framework

Non-residential real estate markets are characterized by the interaction of four sub-markets (Ball et al., 1998):

- Final user market, which comprise a stock of offices at various locations, which office users select from in order to conduct their productive activity. This stock can be rented from the owners of available office space. In turn, these owners will have acquired this property by resorting to the:

- Investment market, whereby institutional or private investors (or even occupants) acquire real estate assets based on their expected performance relative to other assets and their risk profile (opportunity cost). They may have acquired their property by resorting to the second-hand market or to the:

- Development market, whereby new office space is added to the existing stock. New stock is activated when businesses require additional space, in a market with an inelastic short term supply. Indeed, construction can take years, which accounts for the inelasticity of supply. The land on which new office buildings are constructed is acquired on the:

- Development site market, which corresponds to the (limited) locations where the new stock can be developed. The type of building that will be eventually developed depends on the opportunity costs of competing land uses. As such, each potential activity (residential, commercial, industrial, offices, etc.) competes with the others, thereby determining land costs.

This study seeks to analyze the final user market, characterized by the relative scarcity of office stock in relation to current demand. Demand is mainly derived from the need to use this space as a production input, primarily of non-industrial economic activities that require a specific location for their labor force. Among the main activities that require office space, we find:

- Business services sector,
- Financial, insurance and real estate sectors,
- Support for industrial production (management, human resources, etc.), and
- Public Administration.

As is evident, the labor required by these activities, and therefore housed in office buildings, corresponds above all to that of the service sector activities (Wheaton, 1987). This means that the occupied stock (and letting rentals) depends heavily on the service sector employment cycle.

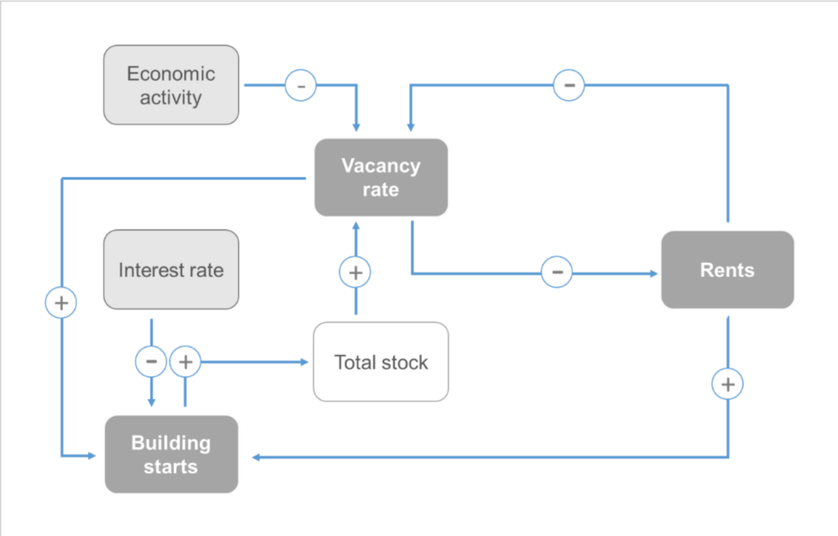
Businesses demand office space from landlords who seek to obtain the maximum return on their investment. According to BNP Paribas Real Estate,[1] 80% of transactions involve offices leases, 5% are pre-lets and the remainder are sales transactions. It is therefore a reasonable assumption in most empirical studies (including this one) that owners exclusively rent space (i.e., they never sell) and end users exclusively let office space (i.e., they never buy). This assumption, moreover, facilitates our analysis, thus allowing us to focus on the dynamics of rents and side-step selling prices.

Office stock has the characteristics of a capital asset, as it is subject to depreciation (via obsolescence or change in use) as well as accumulation (by means of new construction and refurbishment). New stock will be added when

[1] See BNP Paribas Real Estate Spain (2011).

the property prices charged by developers exceed construction costs (including, interest rate, land, construction, material costs, etc.). In other words, after the stock shortage has been transferred to rental increases in the user market, and finally to the selling market, developers will begin the construction of new buildings to benefit from the higher property prices. These developments will cease when the available stock meets all the demand, which causes property prices to return to the level at which the replacement costs are set. In this sense, the office development market can be considered a 'disequilibrium phenomenon' (Ball et al., 1998). Once this disequilibrium is observed in the user market, new stock is added in the next period, thus forming a real estate cycle. Figure 1 presents a conceptual framework proposed by Brooks and Tsolacos (2010) to explain the key relationships of the office market. This theoretical framework is based on a priori treatment of office rent determination put forward in a number of studies (e.g. DiPasquale and Wheaton, 1992; Clapp, 1993; Royal Institution of Chartered Surveyors, 1994; Ball et al., 1998).

Figure 1 An Analytical Model for the Property Market



Notes: Light grey background variables are exogenous, dark grey background variables are endogenous and the white background variable may be determined by calculation.

The direction of the arrows indicates whether a variable affects or is affected by another variable. Two of the variables – the level of economic activity and the interest rate – only affect and are not affected. As such, these can be considered to be exogenous to the model, specifying its partial equilibrium. The sign that accompanies the arrow corresponds to a positive or negative effect of the origin variable on the target variable: for example, an increase in economic activity will reduce the vacancy rate. The endogenous variables, therefore, are the vacancy rate, building starts and rent levels. In the following sections, we specify the equations that can be derived from this model.

Developers will construct new buildings in accordance with the equilibrium between the asset price and their replacement costs. In other words, office supply responds positively to higher property prices and negatively to production costs and financing, which in this study are assumed to be exogenous. Meanwhile, when property prices rise, the available stock becomes scarcer (once the reduction of space per employee has been exhausted); that is, a lower vacancy rate – which is the ratio between the total available floor area and stock – means higher rental values. In turn, this shortage is greater in periods of increased economic activity. In summary, the office market depends positively on the real business cycle and employment. The high correlation between activity variables (production, economic sentiment, etc.) and employment, as well as the correlation between national and local employment allow for similar adjustments in commercial real estate models. According to Brounen and Jennen (2009a) no significant differences are obtained. Nevertheless, here we test our models both for national and local activity variables; in short, we model the office market in Madrid with both the gross domestic product (GDP) of Spain and the service sector employment level of Madrid.[2] Both give similar results, thus confirming the findings of Brounen and Jennen (2009a).

3. Modelling Strategy

Following Englund et al. (2008, hereafter EGHS) and HJM, we adopt a cointegration approach that employs a single long-term equation among rent, economic activity and stock as ECMs in the three expressions of rent, vacancy rate and stock adjustment. As such, our approach specifies the short run dynamics as a system of the three equations to be solved simultaneously.

The office space demand of businesses is a function of their activity level and the rent level on new contracts:

$$D_t = \gamma_0 R_t^{\gamma_1} E_t^{\gamma_2} \tag{1}$$

where γ_1 and γ_2 are the (negative) price and (positive) income elasticities for the logarithmic expression of Equation (1). The equilibrium rent is reached when the vacancy rate is at its long term (constant) level and demand is equal to the total supply (S_t) minus the natural vacancy level:

[2] Although a clear definition for office employment exists, no such statistical series is found for the period and so frequency is used in this study (2001:Q1 – 2015:Q2).

$$D_t(R_t, E_t) = (1 - V^*)S_t \tag{2}$$

Substituting Equations (1) into (2), we obtain:

$$R_t = \gamma_0 ' E_t^{\gamma_1} \left[(1 - V^*) S_t \right]^{\gamma_2} \tag{3}$$

which corresponds to our expression of the long-run rent, and may be expressed in logs as:

$$\ln R_t = \ln \gamma_0 ' + \gamma_1 \ln E_t + \gamma_2 \ln(1 - V^*) + \gamma_2 \ln S_y \tag{4}$$

Equation (4) may be re-expressed by taking into account that $\ln(V^*) = v^*$ is a constant value:

$$\ln R_t = \gamma_0 + \gamma_1 \ln E_t + \gamma_2 \ln S_y \tag{5}$$

where $\gamma_0 = \ln\gamma_0' + \gamma_2 \ln(1 - v^*)$. Note that because $\ln\gamma_0'$ is unknown, the natural vacancy rate cannot be solved from this expression (HJM). Nevertheless, the value can be derived from the short run expressions.

The short run expressions for our modelling are standard for the dynamics under ECMs:

$$\begin{aligned} \Delta \ln R_t = \alpha_0 &+ \sum_{i=0}^{n_1} \alpha_{1,i} \Delta \ln R_{t-i} + \sum_{i=0}^{n_2} \alpha_{2,i} \Delta \ln E_{t-i} \\ &+ \sum_{i=0}^{n_3} \alpha_{3,i} \Delta \ln S_{t-i} + \sum_{i=0}^{n_4} \alpha_{4,i} v_{t-i-1} + \sum_{i=0}^{n_5} \alpha_{5,i} \varepsilon_{t-i-1} \end{aligned} \tag{6}$$

In Equation (6), the vacancy rate adjustment term does not contain the long term level for this rate, as it is constant and embedded in the constant term. In fact, if we depart from this constant term, we can estimate the long term (or natural) level of the vacancy rate knowing that $\alpha_0 = -v^* \sum_{i=0}^{n_4} \alpha_{4,i}$, therefore: $v^* = -\alpha_0 / \sum_{i=0}^{n_4} \alpha_{4,i}$

Taking Equation (6) as our reference, we can specify the short run dynamics for the vacancy rate:

$$\begin{aligned} \Delta v_t = \beta_0 &+ \sum_{i=0}^{m_1} \beta_{1,i} \Delta v_{t-i} + \sum_{i=0}^{m_2} \beta_{2,i} \Delta \ln E_{t-i} + \sum_{i=0}^{m_3} \beta_{3,i} \Delta \ln S_{t-i} \\ &+ \sum_{i=0}^{m_4} \beta_{4,i} \Delta v_{t-i-1} + \sum_{i=0}^{m_5} \beta_{5,i} \Delta \varepsilon_{t-i-1} \end{aligned} \tag{7}$$

From Equation (7) it is also possible to estimate the natural value of the vacancy rate with $\beta_0 = -v^* \sum_{i=0}^{n_4} \beta_{4,i}$, so $v^* = -\beta_0 / \sum_{i=0}^{n_4} \beta_{4,i}$.

The short run adjustment of the stock level is estimated by means of the gap between the natural and the actual vacancy rates. The rationale for this is derived from the idea that greater gaps mean higher rents. At the same time, HJM assert that the present value of expected future rents is the value of new stock investment, or the change in office stock, which is in fact our third short term equation. This is a useful specification for our study as we lack series of new deliveries and stock destruction or depreciation. The stock adjustment is, therefore, as follows:

$$\Delta S_t = \delta_0 + \sum_{i=0}^{l_1} \delta_{1,i} \Delta S_{t-i} + \sum_{i=0}^{l_2} \delta_{2,i} v_{t-i-1} + \sum_{i=0}^{l_3} \delta_{3,i} \varepsilon_{t-i-1} \quad (8)$$

where again $-\delta_0 / \sum_{i=0}^{l_2} \delta_{2,i}$ is an estimation of the long-run vacancy rate.

For Equations (6) to (8), the signs are expected to be negative for the ECM estimated coefficient and the variables are expected to return to equilibrium when rents and the vacancy rate are above the long-term value.

4. Database and Variables

The office market database employed in this study is provided by BNP Paribas Real Estate and contains quarterly observations from 2001:Q1 to 2015:Q2. The variables of exogenous economic activity are drawn from the website of the Spanish National Statistics Office (INE). The geographical area of our study is delimited by offices within the Madrid metropolitan area, plus the municipalities of Las Rozas de Madrid, Pozuelo de Alarcón, Alcobendas and San Sebastian de los Reyes. The database conveniently covers two cycles of the Spanish economy: the aftermath of the dot-com crisis, the Great Recession 2007-2013 and the recent recovery phase (2014-2015).

The most common application of cointegration is to test the existence of long-run relationships. One argument sometimes made is that cointegration is about long-run economic relationships, and one needs really long time series (not in the number of observations but in time span; see Hakkio and Rush (1991)) to use cointegration techniques. Maddala and Kim (1998) stress that the length of the long run depends on the speed of adjustment of the particular markets considered, and that the long-run equilibrium relationship needs to have an economic interpretation. We use a sample of 58 quarters (the longest possible period for which reliable and coherent data are available) to test for a cointegrating relationship based on long-run economic relationships in a market with slow speeds of adjustment. Therefore, our empirical results should be taken with caution. Nevertheless, it should be noted that previous contributions in the literature have used similar (or even shorter) time spans and that we will make use of the cointegration procedure that is specifically designed to deal with small data samples.

As discussed above in the modelling section, the system integrates one economic activity variable. There is a certain degree of flexibility when selecting the economic drive of a model given the high correlation between activity variables (including, production and economic sentiment, among others) and employment, as well as the correlation between national and local employment. This enables us to obtain similar adjustments in the commercial real estate models. Using this framework, we estimate two sets of models: one using the GDP of Spain as our economic activity variable; the other using service sector employment in Madrid in order to identify the best model and also to obtain information on the exposure of the business environment of Madrid (office market) to national macroeconomic indicators (GDP of Spain). Table 1 presents the main statistics of the variables used in this study.

The real rent in Table 1 corresponds to the quarterly average headline rent in Madrid for new letting contracts. It is measured in €/m²/month and expressed in real terms at 2010 prices, by using a GDP deflator. The values in parentheses record the periods for which extreme observations are obtained. Maximum values were recorded in 2008 in the case of the GDP, service sector employment and occupied space, thus reflecting the peak in the expansion of the economy and real estate markets of Spain and Madrid. Following the bursting of the bubble, economic activity went into decline, which led to a reduction in rents as well as in occupancy. Rents fell to their lowest point in 2015:Q1, the same quarter that the vacancy rate and the amount of vacant space reached their maximum levels. Figure 2 provides a clearer picture of the recent property cycle in Madrid.

The maximum levels of service sector employment and the GDP were recorded in the second half of 2008, which coincided with the maximum historical levels in occupied space and the lowest vacancy rate (after 2005:Q1). After that date, the occupancy rate fell and the vacancy rate rose rapidly. Just before the last crisis hit the economies of Spain and Madrid, office stock was increasing at an average rate of almost 60,000 m² per quarter, but demand was such that it managed to generate a positive net absorption and a fall in the vacancy rate (7% in 2007:Q2). After 2008:Q2, with the economy shrinking, the rent charged on new letting contracts went into a continuous decline until 2015. With low expectations on returns, developers hastily halted new building starts. However, the delivery of new projects did not come to a standstill as construction can take at least 18 months. This provided a certain degree of momentum to the variation in stock. In the period 2009-2010, this variation was around 55,000 m² per quarter (construction inertia), while from 2011-2015, it was just 7,500 m² per quarter. Figure 2 highlights the common trends described by office rents, the vacancy rate (inversed), economic activity and stock variation. This trend points to a likely common long term growth which, in other words, signals the possible existence of cointegration of these series. The co-movements of the series have been traced via their respective correlations and are shown in Table 2.

Table 1 Main Variables Used in the Empirical Analysis

	Real rent (RENT)	Vacancy rate (VACR)	Office Stock (STOCK)	Spanish GDP (GDP)	Service sector employment (SEMP)	Occupied Space (OS)	Vacant space (VAC)
Unit of measure	€/m^2/month	%	m^2	Index 2010=100	000 persons	m^2	m^2
Mean	18.3	10.4	10,845,798	95.8	2,259.4	9,688,903	1,156,896
Median	18.0	9.5	11,163,405	97.5	2,343.5	9,998,857	993,293
Max	29.7	16.3	11,885,563	104.4	2,515.0	10,332,478	1,933,485
	(2001 Q2)	(2015 Q1)	(2013 Q1)	(2008 Q2)	(2008 Q4)	(2008 Q1)	(2015 Q1)
Min	13.0	3.0	8,493,109	82.5	1,802.0	8,240,115	252,994
	(2013 Q2)	(2001 Q1)	(2001 Q1)	(2001 Q1)	(2001 Q1)	(2001 Q1)	(2001 Q1)
Std. Deviation	3.9	3.9	1,035,969	6.0	216.7	636,415	504,466
Observations	58	58	58	58	58	58	58

Notes: Terms in parentheses are those used in the econometric specification. Real rent has been deflated with Spanish GDP deflator at 2010 constant prices. From the left, the first three variables comprise our endogenous variables, GDP and employment comprise the separate exogenous variables and the last two variables are based on the vacancy rate and office stock.

Figure 2 **Trends in Main Variables Used to Model Office Market in Madrid**
(Times Series Span: 2001:Q1–2015:Q2)

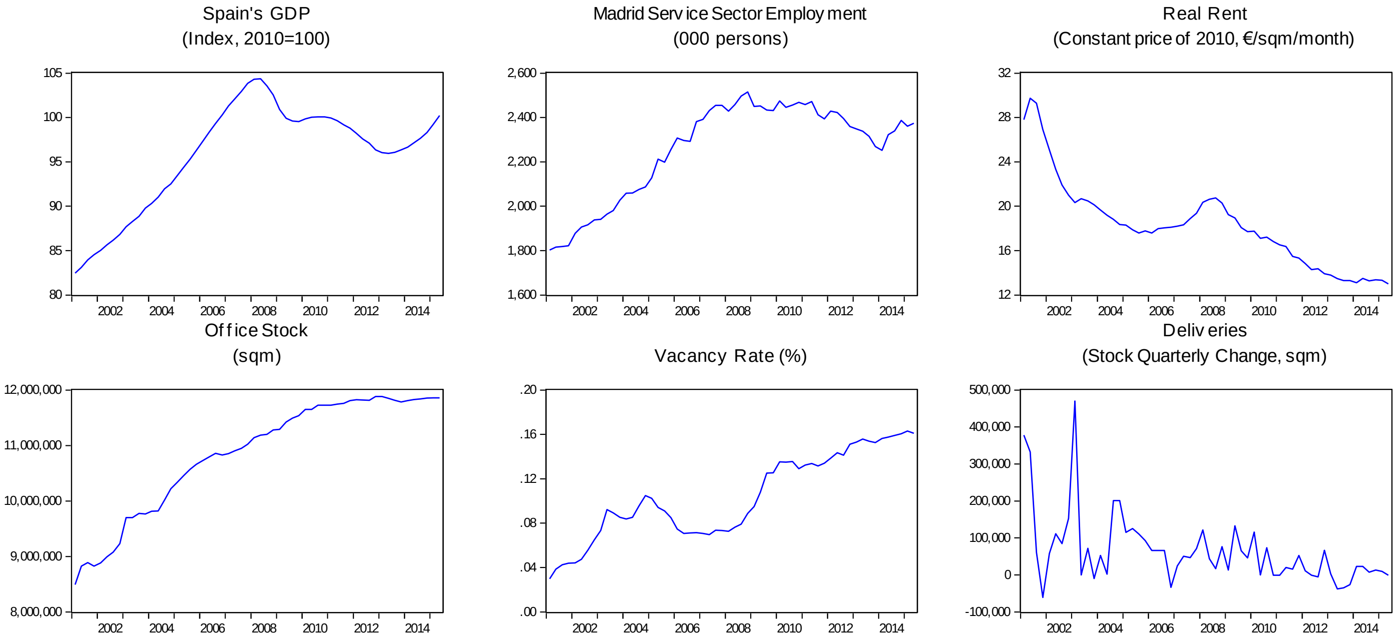


Table 2 **Correlation Analysis**
(Sample: 2001:Q1 – 2015:Q2. Number of observation: 58**)**

Correlation *p-value*	Rent	Vacancy rate	Office stock	Spanish GDP	Service sector employment	Occupied space	Vacant space	Variation in stock
Rent	1.0000							

Vacancy rate	-0.8992	1.0000						
	0.0000	----						
Office stock	-0.8624	0.8535	1.0000					
	0.0000	*0.0000*	----					
Spanish GDP	-0.5942	0.4707	0.8413	1.0000				
	0.0000	*0.0002*	*0.0000*	---				
Service sector employment	-0.6712	0.5914	0.9112	0.9705	1.0000			
	0.0000	*0.0000*	*0.0000*	*0.0000*	----			
Occupied space	-0.6947	0.599702	0.9281	0.9635	0.9810	1.0000		
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	----		
Vacant space	-0.8946	0.9962	0.8828	0.5122	0.63356	0.6443	1.0000	
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	----	
Variation in stock	0.4856	-0.4492	-0.4979	-0.4221	-0.4541	-0.4458	-0.4601	1.0000
	0.0001	*0.0004*	*0.0001*	*0.0010*	*0.0003*	*0.0005*	*0.0003*	----

The correlations among rent, vacancy rate and stock with the proxies of economic activity (GDP of Spain and service sector employment in Madrid) are strong (with the exception of the vacancy rate and GDP). This supports their role as the main drivers, although this awaits the confirmation of the results of the cointegration tests. They are also an indicator of the fact that the series are non-stationary.[3] The correlation of -0.9 between the average real rent and the vacancy rate (p-value of zero) establishes the strong interplay between the real estate variables. Although this correlation is high, it does not equal one, owing to the existence of rigidities in the office space markets. These rigidities are mainly in the form of lease contracts (Wheaton et al., 1997 and HJM), which cause businesses to diverge from their optimal space demand when they receive activity shocks. Another factor might be the role played by structural vacancy, that is, the office stock in which quality, location and access mean their inability to compete on the market (Remøy, 2010).

New deliveries present no strong correlations with the selected variables. Indeed, the high volatility of the series reduces their correlation with the other fundamentals.

5. Econometric Specifications

In order to implement our cointegration regression analysis, we test the variables in the ECM for stationarity. Table 3 summarizes the results.

All the variables included in the cointegrating equation have a unit root in their levels. However, the augmented Dickey-Fuller test fails to reject the hypothesis of the first degree integration for the GDP. The reason for this is that the last crisis linked several quarters of negative variations. Nevertheless, we proceed to test for stationarity with a structural break by using the Perron test (Ng and Perron, 1995). As expected, we reject the null hypothesis for the difference of the GDP, so we can conclude that the GDP level has a unit root when a structural break is accounted for in 2007:Q4, when the Spanish crisis started. We could have opted to include this structural break in our modelling by using a dummy variable, taking a value of zero before 2007:Q4 and a value of one after that date. Nevertheless, from theory, we know the long term relationship between office rents in local markets and national GDP, especially for capital cities, such as Madrid. Using this framework, we do not include this dummy and so employ a simpler modelling of the long term equations.

After determining the order of integration of the variables in the cointegrating equation, we test them for cointegration.

[3] If, on the contrary, the series are stationary, the correlation would be around 50%, which is no more than the correlation given by ‘the flip of a coin’.

Table 3 Integration Test Results

Panel A: Augmented Dickey Fuller (ADF) Test (Null Hypothesis: Series Has Unit Root)

	lag (AIC)	Model	t-Statistic	Critical value (5%)	Critical value (1%)
RENT	5	Constant	-1.2838	-2.9126	-3.5482
ΔRENT***	3	Constant	-3.8438	-2.9126	-3.5482
STOCK	6	Constant + Trend	-1.3657	-3.4892	-4.1242
ΔSTOCK***	5	Constant + Trend	-6.8113	-3.4892	-4.1242
GDP	9	Constant	-1.7763	-2.9126	-3.5482
ΔGDP	8	Constant	-1.5002	-2.9126	-3.5482
SEMP	0	Constant	-2.5791	-2.9126	-3.5482
ΔSEMP***	0	Constant	-6.6930	-2.9126	-3.5482

Panel B: Perron Test with Structural Break (Null Hypothesis: Series Has Unit Root with a Structural Break)

	lag	Model	t-Statistic	Critical value (5%)	Critical value (1%)	Date of structural break
GDP	4	Constant	-4.3343	-5.23	-5.92	NA
ΔGDP***	3	Constant	-6.1336	-5.23	-5.92	Q4 2007

Notes: *** denotes significance at 1% level of confidence. ADF gives strong evidence for first order of integration for rent, stock and service sector employment in Madrid. Evidence for first degree of stationarity for GDP is given by the Perron test, with a structural break in 2007:Q4.

Using both the Johansen (1991) test and the Engle-Granger (1987) single equation cointegration test, we identify at least one cointegrating relationship, i.e., a long run equilibrium relationship among our non-stationary variables RENT, STOCK, GDP or RENT, STOCK, SEMP (see Table 4).

All the tests indicate the presence of a long term relationship among office rents, GDP and office stock on the one hand, or among office rents, service sector employment in Madrid and office stock on the other hand, at traditional confidence levels. It should perhaps be stressed that the Engle-Granger test for Rent, GDP and STOCK is the least indicative of cointegration, whether or not we employ a dummy variable to represent the shock of the 2007 crisis. In contrast, the Johansen test for the same variables supports the presence of cointegration.

Table 4 Cointegration Test Results

Panel A: Johansen Cointegration Test among Rent, GDP and Stock
P-values for the cointegration rank test; Cointegration regression with constant term and 1 to 4 lag interval

		Null hypothesis of:		
		No cointegrating equations	One cointegrating equation	Two cointegrating equations
Cointegration test using	Trace	0.0000***	0.0789*	0.4713
	Maximum eigenvalue	0.0000***	0.649*	0.4713

Notes: Both the trace and maximum eigenvalue tests reject the presence of two cointegrating relationships at the 5% confidence level. This supports the presence of one cointegrating relationship.

Panel B: Johansen Cointegration Test among Rent, SEMP and Stock
P-values for the cointegration rank test; Cointegration regression with constant term and 1 to 4 lag interval

		Null hypothesis of:		
		No cointegrating equations	One cointegrating equation	Two cointegrating equations
Cointegration test using	Trace	0.0000***	0.0664*	0.7882
	Maximum eigenvalue	0.0000***	0.0288**	0.7882

Notes: The trace test rejects the presence of two cointegrating relationships at the 5% confidence level. The maximum eigenvalue test rejects the presence of three cointegrating relationships at the 5% confidence level. This supports the presence of either one or two cointegrating relationships.

Panel C: Engle-Granger Cointegration Test among Rent, GDP and Stock
P-values for the cointegration test; Null hypothesis of no-cointegration; with constant term and 7 lags

		RENT	GDP	STOCK
Cointegration test using	Engle-Granger tau-statistic	0.7106	0.5898	0.5788
	Normalized autocorrelation coefficient	0.0014**	0.5569	0.0000***

Notes: Although the Engle-Granger tau statistic fails to reject the hypothesis of no cointegration, the normalized autocorrelation coefficient test signals some degree of cointegration among the series.

Panel D: Engle-Granger Cointegration Test among Rent, SEMP and Stock
P-values for the cointegration test; Null hypothesis of no-cointegration; with constant term and one lag

		RENT	SEMP	STOCK
Cointegration test using	Engle-Granger tau-statistic	0.0509**	0.0492**	0.0301**
	Normalized autocorrelation coefficient	0.0900*	0.0018***	0.0022***

Notes: Both the Engle-Granger tau statistic and the normalized autocorrelation coefficient test reject the null hypothesis of non-existence of cointegration at the 5% confidence level. ***Denotes significance at the 1% confidence level, ** denotes significance at the 5% confidence level and * denotes significance at the 10% confidence level. All variables tested in log-form.

6. Error Correction Models

Given the non-stationarity of the variables, we select two methods to estimate the error correction models: the classical Engle-Granger two-step method (2SECM) and the single-equation ECM (SEECM, Banerjee et al., 1993). Using these methods, the standard assumptions of the asymptotic analysis are valid in the presence of first-order non-stationary and cointegrated series. Drawing inferences from the estimated coefficients is possible because the t-statistics and f-distributions behave optimally. In this sense, structural modelling in a multivariate system is performed by using seemingly unrelated regressions (SUR), as residual terms may be correlated. The system of equations estimated correspond to Equations (6) to (8).

6.1 Two-Step Methodology Estimates

After recognizing a long term relationship in our variables, we estimate the long run equation for rents by using a fully modified least squares (FM-OLS) regression, as proposed by Phillips and Hansen (1990) when OLS estimates yield biased estimated coefficients. The results of estimating Equation (5) are presented in Table 5.

Both expressions similarly explain the long term path for rents with positive GDP and SEMP elasticities. On the other hand, the long term elasticity for STOCK is negative in both equations. The adjusted R-squared value is, as expected, high in regressions with variables in levels that contain a time trend.

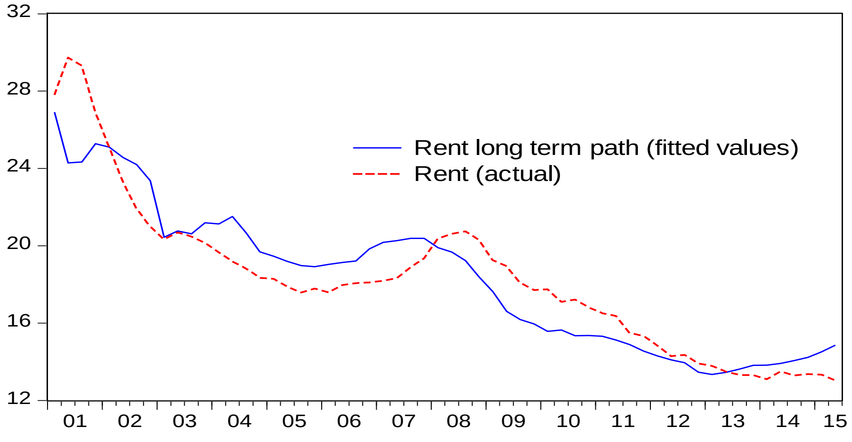
One advantage of estimating a long term expression for prices is the possibility that it affords checking for periods of under- and over-valuation. In Figure 3 we show actual rental prices vs. the estimated long term rent values. In both cases, actual rents present five-year periods of under- and over-valuation. After the dot-com bubble burst, rents were above their equilibrium level. However, after 2002, rents fell and remained below their long term level until 2007, which coincided with the end of the expansion period enjoyed by the Spanish economy. After the outbreak of the last crisis, fundamentals established lower levels of equilibrium rents; however, in the period of 2013 to 2015, rents once again fell below their long term path.

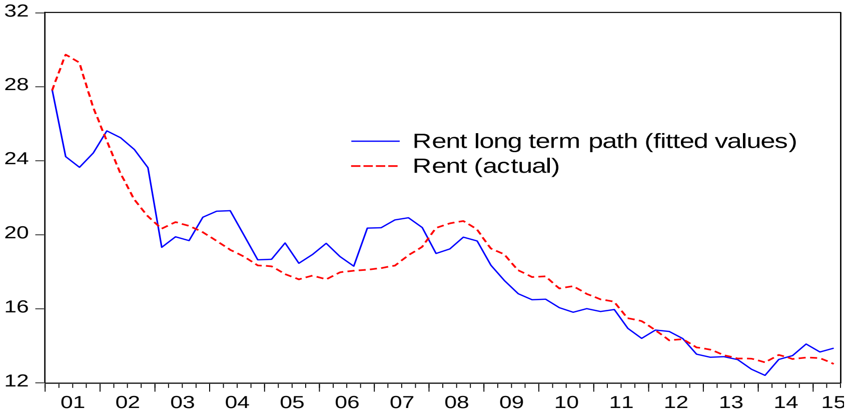
Table 5 Cointegrating Equations

Long run models. Endogenous variable: Logarithm of Real Average Office Rent - LOG(RENT)					
	Coefficient	t-Statistic		Coefficient	t-Statistic
LOG(GDP)	2.3636	5.6574***	LOG(SEMP)	2.4657	7.0437***
LOG(STOCK)	-3.1597	-13.0565***	LOG(STOCK)	-4.1233	-11.7047***
INTERCEPT	4.2766	14.1425***	INTERCEPT	50.6283	15.0515***
Adjusted R-squared	0.8372			0.8642	
Durbin-Watson stat	0.2490			0.5637	
Jarque-Bera (p-value)	0.1949			0.4427	

Notes: Cointegrating equation estimated by FM-OLS, by using Spanish GDP and service sector employment (SEMP) as regressors for the long term expression for average rents. *** Denotes significance at the 1% confidence level; Sample 2001:Q1 – 2015:Q2; No. of observations: 58

Figure 3 Long Run Rent Estimation with Use of Cointegrating Equations in Table 5





The relationship between the long term rent and the actual values is similar in the two models estimated. However, the levels are different. When using Spanish GDP as the regressor for the cointegrating equation, the average over-valuation is 8%, whereas when using SEMP as the regressor, the average over-valuation is 6%. Periods of under-valuation when using both the GDP and SEMP present an average deviation of 6%. The estimated ECM is presented in Table 6.

We estimate two systems of short run equations for average office rent. One uses Spanish GDP in the cointegrating equation and in the short term dynamics; the other uses the service sector employment in Madrid (SEMP hereafter). Drawing on a database of quarterly observations, we restrict the model to a maximum of eight lags, given that in the real estate literature it is common to include an additional two years to capture construction dynamics since it takes this length of time to deliver new buildings to the market.[4] In obtaining the final models presented in Table 6, we use a backward procedure, which progressively omits all insignificant estimators from a general specification (Krolzig and Hendry, 2011).

The adjusted R-squared values range from 53% to 66%. The lowest values are obtained in the estimations of the changes in vacancy rate and stock when using SEMP as the proxy of economic activity (53% in both cases). The equations of variation of the vacancy rate with GDP as the proxy of economic activity present the highest value (66%). The adjustment mechanisms (rent and vacancy

[4] We also run a lag structure test by using a simple vector autoregression (VAR) model. Most of the criteria used with the GDP specification point to a lag structure of eight lags while the SEMP specification has a less homogeneous structure with two criteria that point to a structure of eight lags, one to a structure of seven lags and two to a structure of two lags. In order to select the number of lags on the VAR, we use the Akaike, Schwarz and Hannan-Quinn information criteria. The results are not shown here to save space, and available from the authors upon request.

rate ECMs) present the expected negative sign; however, the speed of adjustment is not the same. Serial correlation between residuals does not seem to pose a problem, as the Durbin-Watson statistic is always within the acceptable range of 1.5 to 2.5. In order to test for autocorrelation of higher orders, we use the portmanteau test (Ljung and Box, 1978). As our modelling takes up to eight lags into account, we explore residual serial correlation up to that lag plus a further four periods. The results of the portmanteau (Q) statistic (H0: no serial correlation) reject the null hypothesis for lags tested (the results are available from the authors upon request).

Table 6 ECM Estimates (2SECM)

Panel A: Spanish GDP as Demand Proxy
Short run models. Estimation method: Seemingly Unrelated Least Squares (SUR)

	Coefficient	t-Statistic	P-value
Rent - DLOG(RENT)			
INTERCEPT	-0.0423	-2.0963	0.0377
DLOG(RENT(t-1))	0.4973	5.7388	0.0000
DLOG(RENT(t-6))	-0.1974	-2.2241	0.0276
DLOG(STOCK(-6))	-0.6107	-1.9435	0.0537
LOG(VACR(t-1))	-0.0166	-1.9634	0.0514
$ECM_{REnt}(t-1)$	-0.1545	-4.1598	0.0001
Adjusted R-squared	0.5453		
Durbin-Watson stat	1.9334		
Vacancy - DLOG(VACR)			
INTERCEPT	-0.1618	-4.5187	0.0000
DLOG(VACR(-1))	0.4078	3.7170	0.0003
DLOG(STOCK(-1))	2.4988	3.3974	0.0009
DLOG(STOCK(-2))	-2.4176	-3.0834	0.0024
DLOG(GDP(-1))	-4.4476	-2.9856	0.0033
LOG(VACR(-1))	-0.0824	-5.0580	0.0000
$ECM_{RENT}(t-1)$	-0.1634	-1.6546	0.1000
Adjusted R-squared	0.6656		
Durbin-Watson stat	2.2416		
Stock - DLOG(STOCK)			
INTERCEPT	-0.0123	-2.7036	0.0076
DLOG(STOCK(-7))	0.3286	3.4618	0.0007
VACR(-4)	-0.0064	-3.4130	0.0008
$ECM_{RENT}(t-2)$	-0.0428	-4.0800	0.0001
Adjusted R-squared	0.5344		
Durbin-Watson stat	1.8802		

Panel B: Madrid Service Sector Employment as Demand Proxy
Short run models. Estimation method: Seemingly Unrelated Least Squares (SUR)

	Coefficient	t-Statistic	P-value
Rent - DLOG(RENT)			
INTERCEPT	-0.0681	-2.9805	0.0033
DLOG(RENT(t-1))	0.4511	5.1460	0.0000
DLOG(RENT(t-6))	-0.3589	-3.9902	0.0001
DLOG(STOCK(t-4))	-0.9690	-2.9812	0.0033
VACR(t-1)	-0.0280	-2.8327	0.0052
ECM_{REnt}(t-1)	-0.1116	-3.1189	0.0022
Adjusted R-squared	0.6352		
Durbin-Watson stat	2.1227		
Vacancy - DLOG(VACR)			
INTERCEPT	-0.1214	-2.8351	0.0052
DLOG(VACR(-1))	0.3331	3.0314	0.0028
DLOG(STOCK(-1))	2.1559	2.5695	0.0111
DLOG(SEMP(-1))	-1.5584	-2.9630	0.0035
DLOG(SEMP(-4))	-1.0053	-1.8813	0.0618
LOG(VACR(-1))	-0.0592	-3.0681	0.0025
ECM_{RENT}(t-1)	-0.2429	-2.5986	0.0103
Adjusted R-squared	0.5309		
Durbin-Watson stat	1.7279		
Stock - DLOG(STOCK)			
INTERCEPT	-0.0106	-2.4348	0.0160
DLOG(STOCK(-7))	0.2764	2.9641	0.0035
LOG(VACR(t-4))	-0.0058	-3.2384	0.0015
ECM_{RENT}(t-2)	-0.0492	-5.0439	0.0000
Adjusted R-squared	0.5825		
Durbin-Watson stat	2.1158		

Notes: Sample 2001:Q1–2015:Q2; No. of observations: 58; Total no. of system observations: 174

Rental dynamics: When the GDP is the chosen activity variable, the rent ECM is higher than when SEMP is selected. Specifically, the rent deviations from the long term equilibrium are adjusted by 15% each quarter when modelling with the GDP and 11% each quarter when using SEMP. The speed of adjustment is most often measured by the half-life, that is, the time needed in order to eliminate 50% of the deviation[5]. Using this approach, our results indicate that, all other factors being equal, rent deviations are offset in 9 quarters (or 26.9 months) when modelling with GDP and in 12.4 quarters (or 37.3 months) when

[5] The half-life is calculated as follows: $t_{half\text{-}life} = \frac{\ln 2}{\gamma}$ where γ is the estimated ECM coefficient.

using SEMP. Therefore, our results suggest a slow adjustment with rents really wander off from its equilibrium path for extended periods (between 2.2 and 3.1 years), consistent with the anecdotal evidence observed in reality which indicates sluggish price adjustments. This finding would suggest the presence of hysteresis (i. e., history dependence) that, during bullish episodes could reinforce the upward trend and during bearish episodes could delay the necessary adjustment. The vacancy rate adjusts more rapidly when SEMP is used, but the respective coefficients present similar magnitudes: 2.6% each quarter when modelling with job market figures and 1.6% each quarter when using national output. Rent variations are also negatively dependent on stock variation and rent lags in both specifications. At the same time, both GDP and SEMP variations are significant for rent dynamics, the main impact being derived from the ECM.

Vacancy rate dynamics: Both approaches respond in a similar fashion to their own first lag and present a strong positive response to the first lag of stock variation. The variation in economic activity negatively impacts vacancy rate variations and it is important to stress the values of these elasticities: thus, GDP modelling yields a strong impact of economic activity on vacancy rate dynamics of around -2.41 points. In contrast, SEMP variations impact with the first (-1.5) and fourth lags (-1.0). The vacancy rate log-level presents a greater impact when GDP is used in the model (8%) than when SEMP is used (6%). When checking the rent ECM on vacancy rate variation, we obtain a more rapid adjustment with the SEMP model (24% each quarter) than when GDP is used (16% each quarter). The estimated coefficients associated with the ECM suggest that vacancy deviations are offset in 8.5 quarters (or 25.5 months) when modelling with the GDP and in 5.7 quarters (or 17.1 months) when using SEMP. This would imply that the existence of severe impediments for an efficient search and matching between market participants as theoretically studied by Hanushek and Quigley (1979) and Weinberg et al. (1981). As pointed out by Wheaton (1990), uncertainty, transaction costs, market imperfections and costly searches can influence the behaviour of market participants, thus leading to a gradual "disequilibrium" that evolves between units and occupants.

Stock dynamics: Supply equations are the system’s most parsimonious ones and their main components are the vacancy rate and rent gap mechanisms. In both cases (GDP and SEMP), the seventh lag of the stock variation plays an important role, with estimated coefficients of 0.33 and 0.28 for the GDP and SEMP, respectively. The rent and vacancy rate correction mechanisms participate with the second and fourth lags, respectively. This means that stock growth, which is a proxy of new deliveries, is affected by the disequilibria observed in the vacancy rate one year previously and in rents two quarters previously. This is in line with HJM, who argue that longer lags of the regressors affect the stock dynamics due to the time that it takes developers to deliver new buildings to the market. Yet, for these authors, the ECM lag is two years. As for the estimated short-run correction terms, our results suggest that stock deviations are offset in 32.4 quarters (or 97.2 months) when modelling with the GDP and in 28.2 quarters (or 84.5 months) when using SEMP. This finding is consistent with the stylized fact in housing markets in continental European countries (see, for e.g., Andrews et al. (2011)) that the supply of housing reacts relatively slowly to changes in both market prices and vacancy (in our case, between 7 and 8 years). Low supply responsiveness tends to exacerbate the price effect of changes in housing demand (e.g. caused by financial and labour markets or demographic shocks) and, in rigid supply environments, increases in housing demand are much more likely to be capitalized into house prices than to spur increases in the quantity of housing. Supply responsiveness depends not only on geographical and urban characteristics, but also on public policies, such as housing market regulations (which in the Spanish case, are very restrictive regarding the land-use) and on the degree of competition in the home construction industry (Barker, 2004), which in Spain is very limited.

6.2 Single-Equation Methodology Estimates

We now proceed to estimate Equations (6) to (8) with the SEECM. Under this framework, we construct a system of equations that can be estimated by SUR in spite of the presence of non-stationary and co-integrated variables. This is possible thanks to the fact that the dependent variables of the system are differenced and so, the estimations of spurious regressions can be omitted (Keele and De Boef, 2004). Table 7 presents the results of the SEECM for both the GDP and SEMP by using the SUR estimation method.

To a great extent, the estimated SEECMs for the GDP and SEMP behave similarly. However, note that the adjusted R-squared values are lower than those obtained with the 2SECM. This is attributable in part to the fact that the coefficients of the long term deviations are simultaneously estimated, thus decreasing the degrees of freedom. It might also be derived from the fact that each long term coefficient is actually estimated in each variation equation. The adjusted R-squared values now range between 37% and 61%, which is lower than those obtained with the 2SECM. Yet, the adjusted R-squared values are uniform for the three equations with the SEMP approach, which range from 50% to 55%.

Rental dynamics: When modelled with the GDP, rent variation depends on its one quarter lagged value as well as the first lag of stock variation. This coefficient presents a negative value. The coefficients of the rent and vacancy rate correction mechanisms also present negative values. In contrast, when using SEMP as the demand proxy, the same variables are significant for the model, although the change in the exogenous economic driver (SEMP) appears with its sixth lag. As for the correction mechanisms, the mechanism derived from the rent gap suggests a speed of adjustment of 20% each quarter when using the GDP, which indicates *ceteris paribus*, a complete elimination of a given rent disequilibrium in 6.9 quarters (or 20.7 months). When SEMP is employed as the exogenous demand driver, the speed of correction is 18% per quarter, which means that rent adjustment requires around 7.8 quarters (23.5 months). Therefore, although at a lower magnitude, the results in Table 7 give further support to our previous findings of a slow adjustment in rents as reported in Table 6 and are in line with the existence of price momentum in housing markets as suggested by the pioneering work of Case and Shiller (1989). Finally, for the vacancy rate gap, rents are offset 3% by the vacancy rate each quarter, in both the GDP and SEMP approaches.

Table 7 ECM Estimates (SEECM)

Panel A: Spanish GDP as Demand Proxy

Short run models. Estimation method: Seemingly Unrelated Least Squares (SUR)

	Coefficient	t-Statistic	P-value
Long term coefficients			
LOG(GDP)	1.7250	-3.6755	0.0003
LOG(STOCK)	-2.3085	4.4910	0.0000
Rent DLOG(RENT)			
INTERCEPT	6.4366	3.6970	0.0003
DLOG(RENT(t-1))	0.4825	5.3085	0.0000
DLOG(STOCK(-6))	-0.7894	-2.5205	0.0127
LOG(VACR(t-1))	-0.0299	-1.7986	0.0740
ECM_{REnt}(t-1)	-0.2008	-5.4959	0.0000
Adjusted R-squared	0.5352		
Durbin-Watson stat	2.1423		
Vacancy DLOG(VACR)			
INTERCEPT	10.4803	2.7843	0.0060
DLOG(VACR(-1))	0.2529	2.4458	0.0155
DLOG(GDP(-1))	-6.7335	-5.1831	0.0000
DLOG(STOCK(-2))	2.7215	3.5562	0.0005
LOG(VACR(-1))	-0.1167	-4.1107	0.0001
ECM_{RENT}(t-1)	-0.3311	-3.6296	0.0004
Adjusted R-squared	0.6163		
Durbin-Watson stat	1.6916		
Stock DLOG(STOCK)			
INTERCEPT	1.8383	3.7080	0.0003
DLOG(STOCK(-7))	-0.0146	-3.1777	0.0018
VACR(-4)	-0.0576	-4.0472	0.0001
ECM_{RENT}(t-2)	1.8383	3.7080	0.0003
Adjusted R-squared	0.3879		
Durbin-Watson stat	1.6111		

Panel B: Service Sector Employment in Madrid as Demand Proxy
Short run models. Estimation method: Seemingly Unrelated Least Squares (SUR)

	Coefficient	t-Statistic	P-value
Long term coefficients			
LOG(GDP)	-2.2901	-6.7315	0.0000
LOG(STOCK)	4.0787	7.9061	0.0000
Rent DLOG(RENT)			
INTERCEPT	6.6601	3.1260	0.0021
DLOG(RENT(t-1))	0.5441	5.9162	0.0000
DLOG(STOCK(-1))	0.1452	1.7972	0.0742
DLOG(SEMP(t-6))	-0.5179	-2.1386	0.0340
LOG(VACR(t-1))	-0.0293	-1.6851	0.0940
ECM_{REnt}(t-1)	-0.1772	-4.9275	0.0000
Adjusted R-squared	0.5283		
Durbin-Watson stat	2.3225		
Vacancy DLOG(VACR)			
INTERCEPT	13.7737	2.7133	0.0074
DLOG(VACR(-1))	0.3092	2.7517	0.0066
DLOG(SEMP(-1))	-1.7100	-3.2035	0.0016
DLOG(SEMP(-2))	-0.9775	-1.7835	0.0765
DLOG(STOCK(-1))	2.0910	2.5027	0.0134
LOG(VACR(-1))	-0.0529	-2.1710	0.0314
ECM_{RENT}(t-1)	-0.2707	-2.8148	0.0055
Adjusted R-squared	0.5077		
Durbin-Watson stat	1.5832		
Stock DLOG(STOCK)			
INTERCEPT	3.4493	7.0339	0.0000
VACR(-8)	-0.0069	-1.7633	0.0798
ECM_{RENT}(t-2)	-0.0675	-4.9681	0.0000
Adjusted R-squared	0.5528		
Durbin-Watson stat	2.1251		

Notes: Sample 2001:Q1–2015:Q2; No. of observations: 58; Total no. of system observations: 174

Vacancy rate dynamics: The vacancy rate change depends on its first lag. It also depends negatively on the first lag of both the GDP and SEMP and positively on the second lag of stock (note that both specifications give quite similar outcomes). The rent correction mechanism shows a relatively moderate adjustment of the vacancy rate (33% when using the GDP and 27% when using SEMP, which suggest that vacancy deviations are offset in 4.2 and 5.1 quarters, respectively), thus indicating once again the presence of costly searches associated with the idiosyncratic taste of households and transaction costs. The vacancy rate gap is also similar, with estimated values of 5% in both cases.

Stock dynamics: The stock growth rate depends on the seventh lag of stock when the GDP is used as the demand proxy. When SEMP is employed, stock only depends on the vacancy rate gap in its fourth lag and the rent ECM in its second. The same is found when modelling with the GDP, but in this case, the observation of rent two years previously determines the current variation of stock. Here, the second lag of the rent ECM affects current deliveries. Regarding the values of the estimated ECM coefficients, they suggest that stock deviations are offset in 21.4 quarters (or 72.2 months) when modelling with the GDP and in 20.5 quarters (or 15.4 months) when using SEMP. This relatively rigid responsiveness of housing supply to price changes has potential consequences for the nature and speed of the stock-flow adjustment mechanism that characterizes housing markets, as it discourages residential mobility and increases housing affordability differentials across

6.3 Long Run Vacancies

As discussed in the modelling section, a different definition of the long run vacancy rate is embedded in each of the short run equations. We use the estimated values to retrieve the long run vacancy rate for each equation estimated in the 2SECM but not with the estimations, provided that the information embedded in the constant term also includes the constant of the cointegrating relationship times the adjustment coefficient. Table 8 presents the results.

Table 8 Estimated Values for the Long Run Vacancy Rate
Estimated long run vacancy rates

	Equation to retrieve vacancy rate	Growth equation	GDP as demand proxy (%)	SEMP as demand proxy(%)
Two-step ECM	$v^* = -\alpha_0 / \sum_{i=0}^{n_4} \alpha_{4,i}$	Rent	12.8	11.4
	$v^* = -\beta_0 / \sum_{i=0}^{n_4} \beta_{4,i}$	Vacancy rate	7.1	7.8
	$v^* = -\gamma_0 / \sum_{i=0}^{l_2} \gamma_{2,i}$	*Stock*	6.8	6.1

Notes: Values retrieved as $exp(v^*)$

Although the results are similar when modelling with the GDP and SEMP, they do differ across the growth equations. Thus, they are closer in the case of the vacancy rate and stock equations, which range between 6.1 and 7.8%. As for the rent equations, the long run values are 11.4% and 12.8%, which point to the high value of the stationary vacancy rate in the office market in Madrid. The vacancy rate and stock equation estimates seem more reasonable and are more closely in line with the outcomes in HJM.

To summarize the findings of the estimation, we present the results of the error mechanisms obtained for all the methods used. Table 9 contains the values of the rent and vacancy ECMs.

Table 9 **Summary of Rent and Vacancy ECMs**
Estimated coefficients of error correction mechanisms
(Lags of the correction mechanism in parentheses)

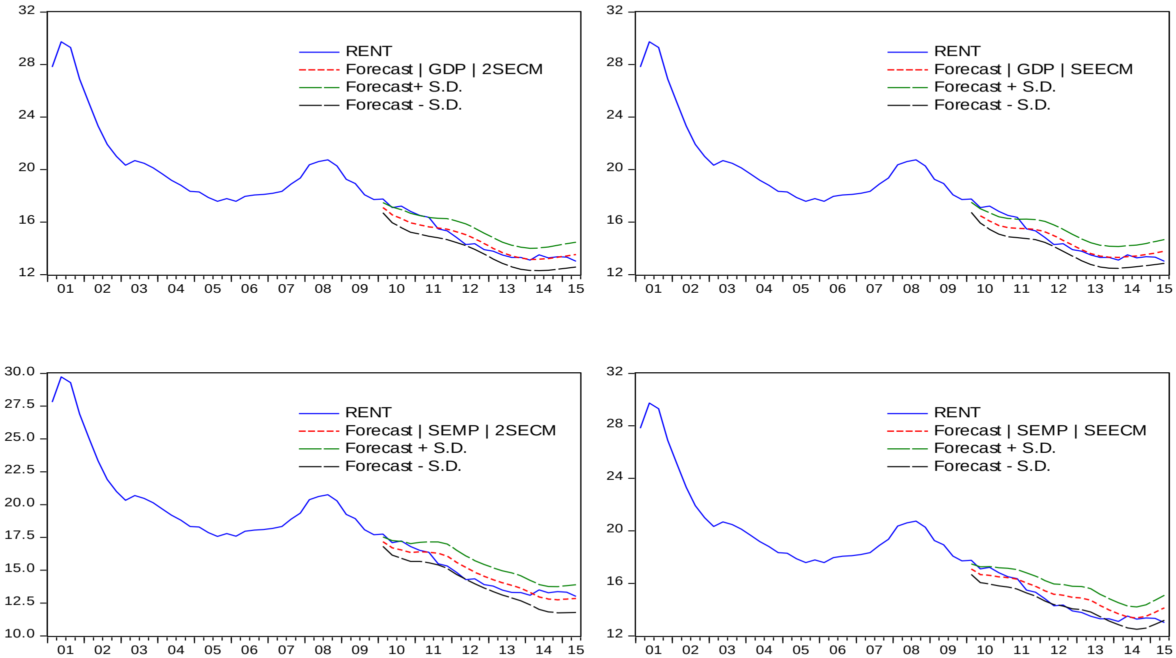
		Growth equation	GDP as demand proxy	SEMP as demand proxy
Two-step ECM	Rent ECM	Rent	-0.1545 (t-1)	-0.1116 (t-1)
		Vacancy rate	-0.1634 (t-1)	-0.2429 (t-1)
		Stock	-0.0428 (t-2)	-0.0492 (t-2)
	Vacancy gap	Rent	-0.0824 (t-1)	-0.0280 (t-1)
		Vacancy rate	-0.0824 (t-1)	-0.0592 (t-1)
		Stock	-0.0064 (t-4)	-0.0058 (t-4)
Single Equation ECM	Rent ECM	Rent	-0.2008 (t-1)	-0.1772 (t-1)
		Vacancy rate	-0.3311 (t-1)	-0.2707 (t-1)
		Stock	-0.0576 (t-2)	-0.0675 (t-2)
	Vacancy gap	Rent	-0.0299 (t-1)	-0.0293 (t-1)
		Vacancy rate	-0.1167 (t-1)	-0.0529 (t-1)
		Stock	-0.0146 (t-4)	-0.0069 (t-2)

Notes: All values are significant at the 5% confidence level.

7 Forecast Performance Comparison

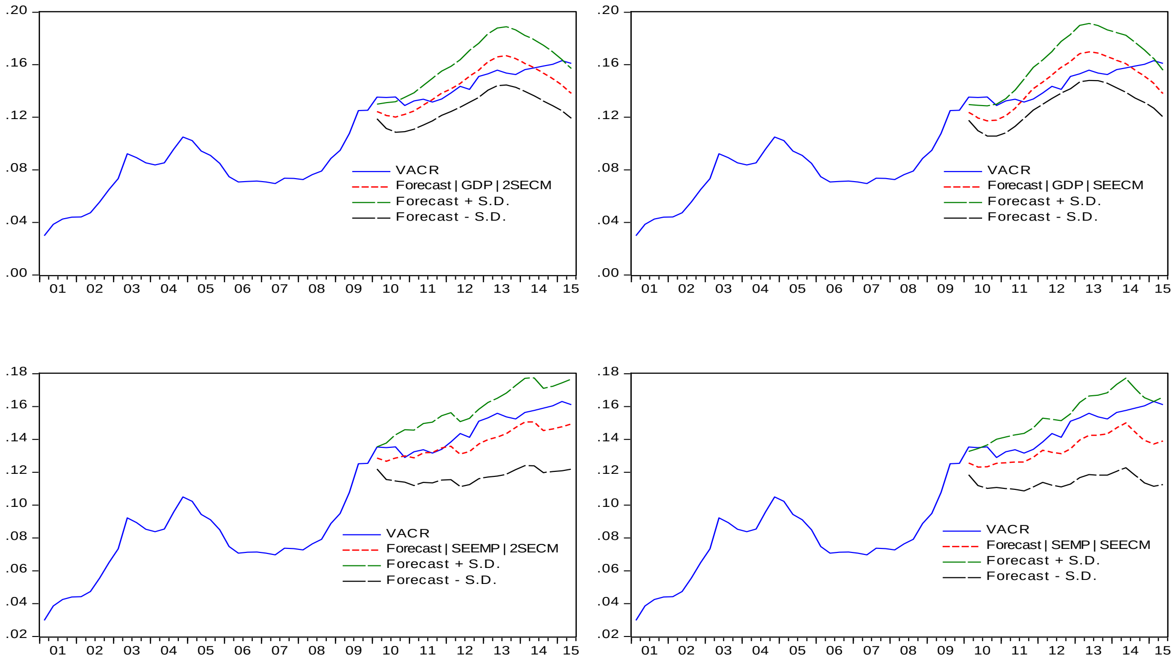
To present an initial illustration of the differences in the forecasting performance of our four models, we present dynamic forecast charts for the period 2010:Q1 to 2015:Q2.

Figure 4 Rent Dynamic Forecasts



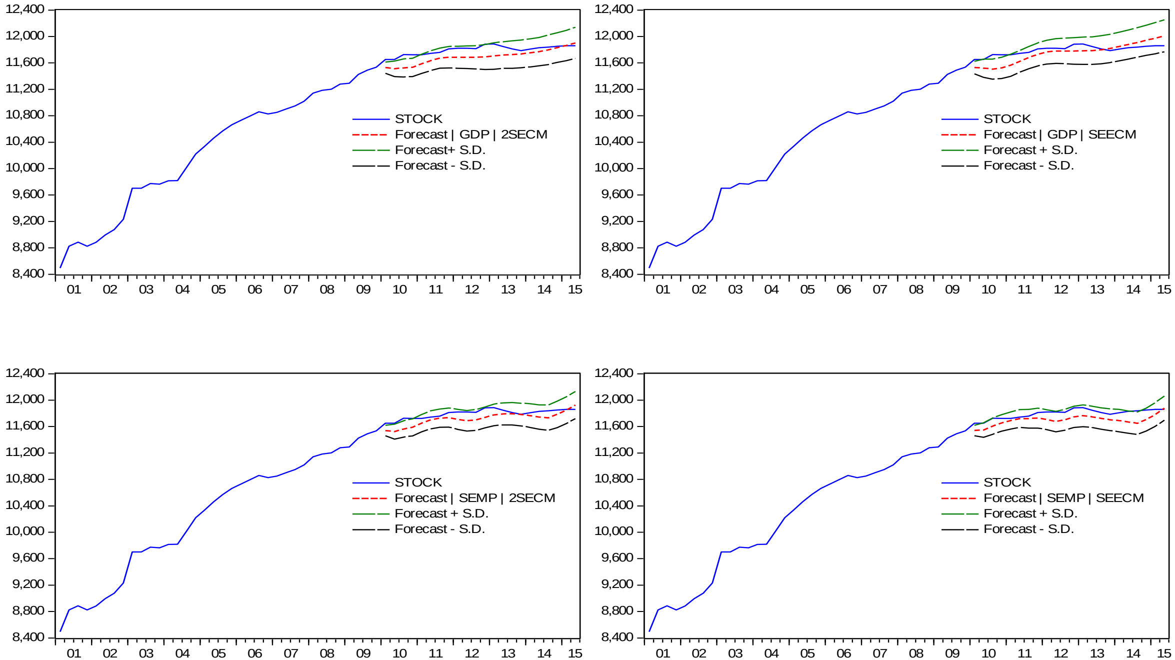
Notes: Rent dynamic forecasts with the four approaches employed. Sample 2001:Q1–2015:Q2; No. of observations: 58; Total no. of system observations: 174.

Figure 5 Vacancy Rate Dynamic Forecasts



Notes: Vacancy rate dynamic forecasts with the four approaches employed. Sample 2001:Q1–2015:Q2; No. of observations: 58; Total no. of system observations: 174

Figure 6 Stock Dynamic Forecasts



Notes: Stock dynamic forecasts with the four approaches employed. Sample 2001:Q1–2015:Q2; No. of observations: 58; Total no. of system observations: 174. The least biased forecasts are those modelled with Spanish GDP.

In general, the models predict a market recovery following the upturn in the Spanish economy in H1 2014. Specifically, rents are forecasted to increase in 2015, as is stock. Meanwhile, the vacancy rate is forecasted to fall in 2015. The goodness of fit appears to be higher in the rent and stock equations, but less so on that of the vacancy rate. We compute the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Theil coefficient (THEIL) for all the forecasts produced in order to obtain a quantitative assessment of forecast performance. Table 10 contains these results in addition to the corresponding scores to help in aggregating the goodness of fit information in a single figure.

As we obtain 48 indicators of forecasting performance, we design a normalized scoring system that allows us to identify the best modelling techniques. Apart from ranking the scores, we devise a measure of relative distance between each statistic by computing the following formula:

$$R_i = \frac{S_i - S_{\min}}{S_{\max} - S_{\min}} ; 0 \leq R_i \leq 1$$

In this ratio, the maximum performance statistic S_{max} takes a value of one $R_i = 1$ and the minimum performance statistic S_{min} takes a value of zero $R_i = 0$. The intermediate performance statistics S_i indicates the relative distance between the maximum and minimum values. This allows us to take into account similar forecast performances of the statistics. In other words, we weight the performance statistics as a function of their relative situation to avoid the homogenous weighting derived from a simple ranking. To aggregate the performance comparison of the individual performance measures, we simply sum the normalized scores and select the one with the lowest value. Table 11 shows the main results of the aggregation of the normalized performance statistics.

Several interpretations can be made of the results in Table 11. If we wish to compare modelling techniques, we need to compare Row 1 with Row 2 and Row 3 with Row 4. By doing so, we can conclude that the 2SECM yields lower scores and so performs better than SEECM. The only exception occurs in the case of the stock equation when using the GDP as the exogenous demand driver. Notice, however, it provides a worse forecast when using SEMP as the exogenous variable.

Table 10 **Forecast Performance Evaluation**

	Rent forecast				Vacancy rate forecast				Stock forecast			
Model	GDP 2SECM	GDP SEECM	SEMP 2SECM	SEMP SEECM	GDP 2SECM	GDP SEECM	SEMP 2SECM	SEMP SEECM	GDP 2SECM	GDP SEECM	SEMP 2SECM	SEMP SEECM
RMSQ*	0.50	0.53	0.55	0.70	1.03	1.30	0.92	1.34	129.29	104.14	88.12	104.37
	0.00	*0.12*	*0.21*	*1.00*	*0.25*	*0.91*	*0.00*	*1.00*	*1.00*	*0.39*	*0.00*	*0.39*
MAE*	0.40	0.39	0.49	0.60	0.86	1.19	0.79	1.20	114.75	89.96	77.39	95.83
	0.03	*0.00*	*0.46*	*1.00*	*0.15*	*0.97*	*0.00*	*1.00*	*1.00*	*0.34*	*0.00*	*0.49*
MAPE	2.58	2.53	3.34	4.22	5.83	8.11	5.27	8.01	0.97	0.76	0.66	0.81
	0.03	*0.00*	*0.48*	*1.00*	*0.20*	*1.00*	*0.00*	*0.97*	*1.00*	*0.34*	*0.00*	*0.49*
THEIL	0.02	0.02	0.02	0.02	0.04	0.04	0.03	0.05	0.01	0.00	0.00	0.00
	0.00	*0.13*	*0.20*	*1.00*	*0.19*	*0.78*	*0.00*	*1.00*	*1.00*	*0.38*	*0.00*	*0.40*

Notes: Low scores indicative of a better performance. The black numbers correspond to the performance statistic obtained for each variable forecast, each modelling approach and both exogenous variables used. The grey numbers correspond to the scoring system employed to aggregate and rate the forecasting performance statistics. *In €/m^2/month for Rent forecast; in % for Vacancy Rate forecast; in 000 m^2 for Stock forecast.

Second, if we wish to compare the relative performances when using the GDP or SEMP, we need to compare Row 1 with Row 3 and Row 2 with Row 4. In this case, the results are mixed. In the partial particular-equation assessment, GDP modelling performs better when using SEECM in all equations. Yet, the forecast performance when using 2SECM is mixed, depending on the specific equation under consideration. If we consider the overall scores (last column in Table 11), the performance is better (lowest score) when using the GDP and SEECM than when using SEMP and SEECM. However, the overall performance is better when using SEMP and 2SECM than when using the GDP and 2SECM. Thus, a comparison of forecast performance from the perspective of exogenous variables is not always clear cut, which means individual researcher criteria are important in deciding which model to use.

Table 11 Results of the Standardized Forecast Performance Statistics

		Variable forecast			
		Rent	Vacancy	Stock	Overall score
Exogenous variable and methodology employed	GDP | 2SECM	**0.05**	**1.27**	5.1	6.4
	GDP | SEECM	0.24	4.66	2.4	7.4
	SEMP | 2SECM	1.34	**1.27**	**0.9**	**3.5**
	SEMP | SEECM	4.00	4.96	2.8	11.7

Notes: We aggregate the results of each performance statistic for each variable in order to obtain the best approach for making predictions. 2SECM performs better than SEECM in the partial 'equation-specific scores' and in the overall score, with the exception of the Stock equation when GDP is used as the exogenous variable.

If we examine single variable forecast performances, the scoring system indicates that combining the GDP and 2SECM is the best approach for predicting rents and vacancy rate. The most suitable approach for making stock forecasts is combining regional SEMP and 2SECM. This last combination also gives good forecasts of the vacancy rate.

Finally, if we only compare the overall scores, the good forecast performances for stock and vacancy rate means the 2SECM combined with the service sector employment (SEMP) in Madrid provides the best approach for forecasting rents, vacancy and stock in a single system.

8 Concluding Remarks

We have modelled the office market in Madrid by using a system of equations for variations in stock, vacancy rate and rental prices (average real rent), within an ECM framework. This framework enables us to capture the long term development paths and, therefore, to analyze short term deviations from the framework. Having rejected the hypothesis of the non-existence of first degree stationarity of the model variables (i.e., rents, vacancy rate, stock, GDP and service sector employment in Madrid), we fail to reject the hypothesis of the non-existence of cointegration, thus establishing a solid basis for co-integration estimation techniques. We employ two approaches to estimate the ECMs: the two-stage ECM (2SECM) and the single-equation ECM (SEECM). The latter application is novel in the context of commercial real estate, while the 2SECM is the classical approach taken in the real estate literature. Indeed, to the best of our knowledge, the SEECM has not been used in studies of real estate to date.

Both techniques are tested by using two exogenous variables that proxy economic activity: Spanish GDP and service sector employment in Madrid. Thus, in total, we fit and compare four models. Our results suggest that the two exogenous economic variables have quite similar explanatory capabilities. When modelling the short run relationships, we produce a robust structure, in which the regressors present a high degree of significance, as well as a high goodness of fit for the four models estimated. In the case of rent dynamics, the economic driver gives feedback through the long term expression, but is also dependent on the lagged value and changes in the stock level. Vacancy rates also depend on their lagged values, as well as on the dynamics of the economic driver (GDP or service sector employment). Stock tends to be the most rigid of the expressions, depending only on its lagged values and the ECM of the vacancy rate and rents.

The speed of adjustment to long term rent gaps and long term vacancy rate gaps present the expected – negative – sign and magnitude in all of the estimated equation systems. Although there is some variation between the models, we can conclude that office rents in Madrid adjust each quarter at around 15% of their deviation from the long term rent equilibrium, thus suggesting relatively sluggish price adjustments. The average adjustment speed of rents to the long term vacancy rate gaps is around 4% in each quarter. The quarterly adjustments of vacancy rates to long term rent gaps and long term vacancy rate gaps are 25% and 7.5%, respectively (thus indicating existence of severe impediments for an efficient search and match between market participants). As for stock, the speed of adjustment is the lowest of the three, which is around 5% in the case of the rent gap and less than 1% in the case of the vacancy rate gaps, thus suggesting low supply responsiveness related to housing policies such as land-use and building regulations, the absence of incentives to encourage the usage of underdeveloped land and the low degree of competition in the construction industry.

Based on the properties of our theoretical equations (Equations (6) to (8) above), we derive a long term vacancy rate or natural vacancy rate values. When using the rent dynamics expression, we obtain values around 12%. However, when using the vacancy rate and short term equations of the stock to solve for the long term vacancy, we obtain values around 7%, which is more in accordance with the related literature (EGHS and HJM). The full sample average vacancy rate is 10.4% and if we use this as our benchmark, then the long term value derived from the vacancy rate and stock equations is more realistic. Likewise, from the perspective of the literature, this value is more in line with a sound office market.

We test our models to dynamically forecast a five-year period. As a general trait, rents and stock forecasts present the lowest levels of error, which means that forecasting vacancy rates is more challenging. Yet, the forecasts from the four models estimated present low levels of errors and fit the actual values of the endogenous variables well (see Table 10).

Finally, we design a comparative scoring system to aggregate the results of the four different forecast performance indices. Using this technique, we posit that the best model for forecasting rent is the 2SECM which uses the GDP as the exogenous economic variable. It should be therefore emphasized that the feedback of an aggregated variable, such as GDP, on local business decisions is strong and worth analyzing. This combination also holds for vacancy rate forecasting. Yet, when forecasting stock, the best results are obtained by using service sector employment (SEMP) in Madrid as our exogenous demand proxy, while continuing to use the 2SECM. Indeed, this last combination constitutes the best approach for estimating the system of three equations, given that its vacancy rate forecasts are as good as those obtained with the GDP and the 2SECM and its forecast error is low in the case of rents.

Although the introduction of the SEECM is innovative, it does not yield consistently better results than the more classical 2SECM. Nor does the former mechanism inform us about the long term vacancy rate, as the constant term of the long run equation (whether significant or not) is embedded in the short run expression.

This study opens up new research paths, most notably the testing of asymmetric shocks and the conducting of impulse-response analyses. Other lines of research worth developing include panel data modelling and the pooling of market data from European capital cities, while extracting the fixed effects of each market apart from classical elasticities.

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Appendices

Appendix I System Residual Autocorrelations
Portmanteau autocorrelation test

Null hypothesis: No residual autocorrelations up to lag h.
Sample: 2001:Q1 – 2015:Q2.
Total no. of observations: 58

GDP as exogenous variable
Estimation method: 2SECM

Lag	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	9.001786	0.4371	9.159712	0.4227	9
2	19.40110	0.3675	19.93043	0.3368	18
3	28.70528	0.3753	29.74212	0.3259	27
4	37.27710	0.4101	38.94888	0.3385	36
5	57.13987	0.1059	60.68549	0.0592	45
6	60.88383	0.2420	64.86145	0.1479	54
7	71.93890	0.2060	77.43389	0.1043	63
8	86.39331	0.1185	94.20100	0.0407	72
9	92.24112	0.1848	101.1229	0.0645	81
10	99.16224	0.2387	109.4859	0.0796	90
11	108.7259	0.2367	121.2879	0.0636	99
12	118.7584	0.2254	133.9375	0.0460	108

SEMP as exogenous variable
Estimation method: 2SECM

Lag	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	7.689030	0.5658	7.823925	0.5520	9
2	18.13213	0.4470	18.63999	0.4143	18
3	29.97563	0.3152	31.12950	0.2659	27
4	39.22844	0.3272	41.06770	0.2581	36
5	58.26080	0.0887	61.89557	0.0479	45
6	64.91047	0.1469	69.31251	0.0783	54
7	72.54845	0.1922	77.99884	0.0966	63
8	84.77159	0.1441	92.17768	0.0548	72
9	95.99469	0.1222	105.4622	0.0353	81
10	100.5885	0.2091	111.0130	0.0658	90
11	113.7219	0.1479	127.2202	0.0295	99
12	125.0850	0.1248	141.5476	0.0168	108

(Continued…)

(Appendix I Continued)

GDP as exogenous variable
Estimation method: SEECM

Lag	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	9.715002	0.3740	9.885440	0.3598	9
2	21.99419	0.2322	22.60317	0.2063	18
3	32.00111	0.2320	33.15593	0.1920	27
4	39.30304	0.3242	40.99874	0.2605	36
5	57.18503	0.1051	60.56771	0.0604	45
6	66.70903	0.1148	71.19063	0.0584	54
7	81.42039	0.0592	87.92120	0.0208	63
8	91.63444	0.0592	99.76950	0.0169	72
9	95.50253	0.1294	104.3480	0.0414	81
10	105.6801	0.1238	116.6460	0.0310	90
11	117.1223	0.1032	130.7661	0.0179	99
12	130.0781	0.0728	147.1017	0.0074	108

SEMP as exogenous variable
Estimation method: SEECM

Lag	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	13.11258	0.1576	13.34262	0.1477	9
2	22.41522	0.2141	22.97750	0.1915	18
3	27.86585	0.4179	28.72544	0.3743	27
4	45.54019	0.1324	47.70899	0.0917	36
5	58.58720	0.0841	61.98685	0.0472	45
6	69.75698	0.0732	74.44545	0.0340	54
7	77.79577	0.0993	83.58761	0.0424	63
8	86.40273	0.1184	93.57167	0.0447	72
9	91.60669	0.1973	99.73147	0.0774	81
10	102.5244	0.1729	112.9237	0.0515	90
11	116.8509	0.1063	130.6032	0.0183	99
12	122.9501	0.1542	138.2936	0.0262	108

Appendix II Lag Order Selection

Exogenous variable: Spanish GDP

Variables: LOG(RENT) LOG(GDP) LOG(STOCK)
Exogenous variables: C
Sample: 2001Q1 2015Q2
No. of observations: 58

Lag	LogL	LR	FPE	AIC	SC	HQ
0	233.6850	NA	7.05e-08	-7.954654	-7.848079	-7.913141
1	560.5647	608.6726	1.22e-12	-18.91602	-18.48973	-18.74997
2	618.7488	102.3238	2.25e-13	-20.61203	-19.86601*	-20.32144
3	627.0284	13.70404	2.32e-13	-20.58718	-19.52144	-20.17206
4	636.8266	15.20409	2.29e-13	-20.61471	-19.22924	-20.07504
5	648.2656	16.56687	2.15e-13	-20.69881	-18.99362	-20.03461
6	671.6561	31.45624	1.35e-13	-21.19504	-19.17012	-20.40629
7	688.6786	21.13130	1.07e-13	-21.47167	-19.12703	-20.55839
8	706.7204	20.53037*	8.33e-14*	-21.78346*	-19.11910	-20.74564*

Notes: * indicates lag order selected by the criterion. LR: sequential modified likelihood ratio (LR) test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. HQ: Hannan-Quinn information criterion

Appendix III Exogenous Variable: Madrid's Service Sector Employment

Variables: LOG(RENT) LOG(STOCK) LOG(SEMP)
Exogenous variables: C
Sample: 2001Q1 2015Q2
No. of observations: 58

Lag	LogL	LR	FPE	AIC	SC	HQ
0	230.2857	NA	7.92e-08	-7.837438	-7.730864	-7.795925
1	498.5961	499.6124	1.04e-11	-16.77918	-16.35288	-16.61312
2	528.7028	52.94621	5.02e-12	-17.50699	-16.76097*	-17.21640*
3	538.9220	16.91456	4.85e-12	-17.54903	-16.48329	-17.13390
4	545.7848	10.64924	5.29e-12	-17.47534	-16.08987	-16.93567
5	555.0545	13.42506	5.35e-12	-17.48464	-15.77944	-16.82043
6	570.1167	20.25608	4.48e-12	-17.69368	-15.66876	-16.90493
7	589.3215	23.84041*	3.29e-12	-18.04557	-15.70093	-17.13228
8	602.0431	14.47636	3.08e-12*	-18.17390*	-15.50954	-17.13608

Notes: * indicates lag order selected by the criterion. LR: sequential modified likelihood ratio (LR) test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. HQ: Hannan-Quinn information criterion